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Road surface classification using automotive ultrasonic sensor

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Abstract

This work examines the method of road surface classification, based on the analysis of backscattered ultrasonic signals. The novelty of our research is the extraction of signal features for separate swathes of illuminated surface (segmentation) and the use of a wide range of statistical methods in real on-road and off-road driving conditions. The errors caused by the influence of environmental conditions and the vehicle movement were analysed, and ways to reduce them were suggested. The results demonstrate the feasibility of reliable surface classification using the proposed methodology.

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Keywords: sonar applications; remote sensing; sensor fusion; classification algorithms; artificial neural networks

1. Introduction

The current demand and still unsolved challenge is to provide remote real-time identification of road surface conditions in both complex environments (off-road terrain, liquid dirt etc.) and weather conditions (rain, spray, fog, snow etc.). In this paper the feasibility of a short-range ultrasonic sensing system is investigated. Along with other sensor technologies such as infrared, radar, LIDAR and visible light [1], the use of ultrasonic signal for surface classification by roughness and surface textures has been investigated in many studies [2-5].

In paper [2] time delay spectrometry and neural networks were used to identify 12 indoor surfaces with different periodic profiles by their frequency response characteristics. A broadband, frequency modulated sonar sensor was

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effectively used to extract information about the geometry and types of certain surfaces in [3]. In [4, 5] the distinguishing between asphalt, grass, gravel, plastic, and carpet was achieved with success rate approaching 100%. The application of ENDURA (Energy-Duration-Range) method [6] allowed differentiation between different types of surfaces by matching measured echo-energy and echo-duration maps with the templates. Sonar performance in distinguishing between surfaces with random and periodic textures has been studied in [7]. In [8] the neural network has been trained to differentiate between wood, carpet, curtain, ceiling, and water covered surfaces. In the most studies the analysis has been made in attempt to distinguish between several surfaces that are typical when using relatively slow mobile robots in a controlled environment. In this paper the most challenging off-road conditions will be investigated, such as driving on gravel, dirt, and grass covered roads, requiring real-time control of the car suspension. In contrast to our previous work [9], in this study we analyze in more detail surface classification using only ultrasonic sensor by means of an extended set of classification algorithms. The factors that influence the accuracy of surface recognition while driving have been discussed.

2. Terrain recognition using statistical classification algorithms

The procedure of surface classification involves a three-stage process: segmentation, feature extraction, and classification. In Fig. 1a the scheme of surface identification in front of the vehicle is shown, where Θ_b =55° is the antenna half power beamwidth, Θ_1=20° is the central grazing angle, and H=0.65 m is the antenna height over ground. In the developed system six signal features were used for surface recognition. Four basic features apply to the entire range from 1.5 m to 4.0 m; they include mean signal power PA (Fig. 1b), signal duration above the threshold DT (Fig. 1c), signal power above the threshold PT (Fig. 1c), and the standard deviation of the signal envelope. Two additional features represent mean power of the signal in the near range (1.5-2.5 m) and in the far range (3.0-4.0 m).

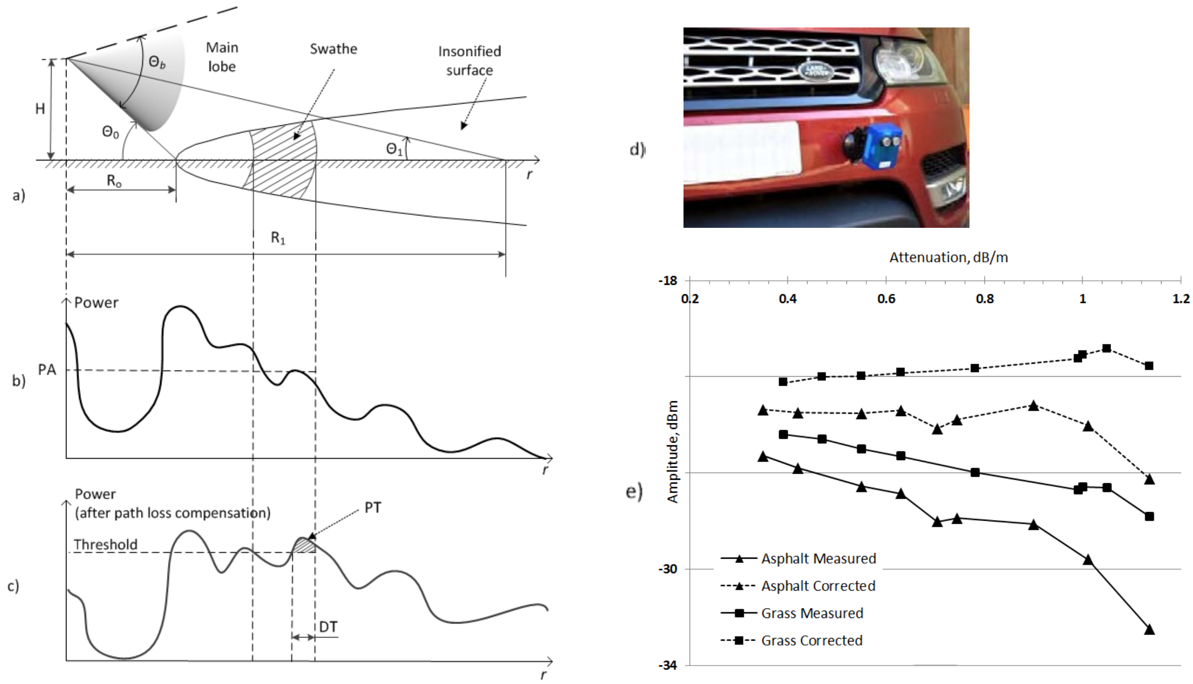

Fig. 1. Surface identification in front of a vehicle using ultrasonic sensor: a) measurement setup, b) power of the backscattered signal, c) power of the backscattered signal after path loss compensation, d) sonar mounted on a vehicle, e) average amplitude of the signal reflected from asphalt and grass in the range from 1.5 m to 4.0 m at different weather conditions: solid lines show the experimental results, dashed lines show the results, environmentally corrected to compensate the signal absorption

The experimental system consists of a sonar sensor coupled to a signal processing module. The sonar (Fig.1d) is based on 40 kHz SRF08 ultrasonic range finder [11], which provides 20 measurements per second with the maximum range of 5 m. The classification was carried out by a dedicated device, based on Arduino micro-controller. The experiments were conducted at different locations near Birmingham, UK to ascertain repeatability of backscattering properties from surfaces related to categories under investigation. The extensive database consists of more than 2500 records of surfaces of practical interest. For road surface identification we applied a method of statistical classification based on four commonly used classification tools (Table 1).

Table 1. Classification methods considered in this work.

Classification method	Acronym
Minimum Distance Classifier using Euclidean or Mahalanobis distance	MDC(E) or MDC(M)
k-Nearest Neighbor (k=3)	KNN
Maximum Likelihood Estimator	MLE
Artificial Neural Network based on Multi-Level Perceptron (3 layers with 4 hidden nodes)	ANN MLP

The results are presented in the Table 2. The performance of MDC is lower than the performance of other methods; however, MDC requires far less computation then other methods. In most cases KNN and MLE methods provide differentiation between asphalt, mastic asphalt, grass, and gravel with the probability of correct classification between 81% and 98%. Dirt road is however very similar to other surfaces in the acoustic properties so its recognition is a more difficult task.

ANN MLP classifier shows the best performance. Another advantage of this method is that it provides minimal variation of the classification accuracy which varies from 81% (grass) to 96% (mastic asphalt). The training of ANN is computationally complex; however the speed of classification using ANN is comparable with the speed of the fastest algorithms.

Table 2. Accuracy of surface classification using different methods.

	MDC(E)	MDC(M)	KNN	MLE	ANN MLP
Asphalt	62%	78%	82%	81%	86%
Mastic asphalt	82%	86%	92%	92%	96%
Grass	64%	64%	74%	77%	81%
Gravel	75%	78%	78%	81%	82%
Dirt road	54%	57%	66%	75%	84%

3. Classification under real conditions

Ultrasonic signals are absorbed by the atmosphere, which could lead to an additional error in the classification of surfaces. The sound attenuation due to atmospheric absorption can be specified in terms of an attenuation coefficient as a function of the frequency of the sound, the temperature, the relative humidity and pressure of the air [12]. In Fig. 1e the amplitude of a signal, reflected from asphalt and grass, is presented as a function of ultrasonic atmospheric attenuation. The measurements were taken at the same locations at different days, the temperature was from 5°C to 13°C, and the relative humidity was from 20% to 80%. Environmental correction of measured backscattering allows better separation between asphalt and grass. When correction of sound attenuation in the air was applied, the average classification accuracy increased by 3.5%. Temperature and humidity sensors, which are equipped with modern cars, can be used as environmental data sources.

While driving in real road conditions, the following factors have significant influence on the measurement accuracy: vehicle pitch and roll; vibrations of the transceiver; reflections from objects on the roadside; reflections from other vehicles; reflections from air fluctuations; uneven absorption of sound waves by air currents.

Our experiments have shown that the change in the grazing angle, caused by a vehicle pitch of $\pm 2°$, results in a change in backscattered signal power for less than half a decibel. Variation of sonar installation height within $\pm 5\,cm$ does not lead to a substantial variation in the power of the reflected signal and in most of practical cases this influence can be neglected. The roll factor has little impact on the measurement accuracy. If we want to reduce errors due to pitch and roll, we must consider the information received from vehicle pitch and roll sensors.

Transceiver mounted on a vibrating vehicle can receive mechanically coupled interface. Our experiments have shown that when ultrasonic sensor is properly mounted on a special damping fixation, this additional noise is low in comparison with the signal and can be neglected. Reflections from roadside objects (buildings, fences, bushes, etc.) can be eliminated by selection of the transceiver beam pattern and by range gating. In addition to range gating, velocity gating can be applied. The velocity of the car in relation to the road is known, which suggests using the Doppler effect to separate the backscattering of the road surface from the moving objects.

The influence of random absorption and reflection of ultrasonic signal caused by air turbulences is much harder to compensate. In particular, the vehicle exhaust gases significantly affect the accuracy of measurements. Our results show that if exhaust gases are directed to the asphalt area, which is the object of measurement, the power of the reflected signal at a distance of two meters may decrease by 3dB. Thus, the measurement error caused by air fluctuations may considerably deteriorate the reliability of surface recognition.

4. Conclusions

In the present study we investigated the classification of a variety of surfaces using ultrasonic sensor. Set of features has been defined to be used in classification. Four common methods of supervised classification were applied for distinguishing between the following types of surfaces: asphalt, mastic asphalt, grass, gravel, and dirt road. Our results have shown that the analysis of the characteristics of the reflected ultrasonic signal allows distinguishing between different road surfaces. Surface identification sonar can be combined with parking sonar sensor due to their very similar principles of operation and structure. However, it is necessary to take additional measures to reduce the error caused by the environmental conditions, movement of the vehicle, and the fluctuations of air currents, which may have a significant impact on the performance of the sonar.

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